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HEALTH POLICY ANALYSIS

Comparing Methods for Identifying Future High-Cost Mental Health Cases in Medicaid

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A B S T R A C T

Objective: This article examines methods for identifying future high-cost cases of Medicaid-covered mental health care services. **Methods:** Florida Medicaid claims data are used to compare methods based on prior cost, and concurrent and prospective diagnosis-based models. Individuals with prior year expenditures in the top decile or with predicted expenditures in the top decile from the diagnosis-based models were expected to be high-cost individuals. **Results:** Individuals in the top decile of prior year costs averaged $13,684 (US dollars) in costs in the following year with 50% remaining in the top decile of spending. Individuals classified as high cost by diagnosis-based models averaged $10,935 to $10,974, with 34% meeting the criteria for a high-cost case in the following year. **Conclusion:** In contrast to research on high-costs cases for physical health care, prior cost was superior to diagnosis-based models at identifying future high cases for mental health care.

Keywords: diagnosis-based models, high-cost users, Medicaid.

Introduction

A high proportion of health care expenditures are concentrated among a small percentage of individuals. Residents of the United States who were in the top decile of health care costs in 2002 accounted for 64% of all expenditures, whereas the bottom 50% of the distribution accounted for only 3% of all expenditures [1]. Health care expenditures are high and remain high over time for individuals with chronic conditions. Forty-one percent of individuals in the top decile in 1 year remain in the top decile in the following year [2], and five conditions (heart, cancer, trauma, mental disorders, and pulmonary conditions) account for nearly one-third of all expenditures [3]. The concentration of spending on relatively few people and conditions is found among both the privately and publicly insured. For example, the 25% of the Medicaid population that is disabled or elderly account for 67% of expenditures [4].

Consequently, several studies have examined methods for the identification of individuals at-risk for high costs [5–7]. Although such studies suggest that prior cost is a predictor of future cost, diagnosis-based models can improve prediction of individuals at risk for high future expenditures. Case managers can use such information to prospectively identify individuals for case review to determine whether they may benefit from additional intervention programs [6]. High-cost cases may offer opportunities for improvements in quality of care and for cost reduction. For example, Kaiser Permanante implemented an assertive community treatment program with identified high-cost users of behavioral health care [8]. Key to implementing such a program is to identify who is at risk for high costs.

Prior research has focused on individuals at risk for high total health care expenditures. Although important, a more detailed examination of expenditures may be warranted. For example, physical health and mental health expenditures should be distinguished when examining high-cost cases in a Medicaid population [9]. Over 30% of individuals in the top decile of total expenditures used mental health services. In addition, the persistence of high costs was a function of mental health diagnoses [10]. Individuals diagnosed with anxiety disorders continued to have high costs in the following year, but individuals with depression and alcohol disorders were less likely to have high costs.

Most diagnosis-based models were developed to predict total health care cost (both physical and mental), and have been found to under-predict costs for individuals with mental health diagnoses [11]. Recent efforts developed models for behavioral health care using private employer data [11] or Veterans Health Affairs (VHA) data [12,13]. The psychiatric models had good predictive power and models developed with private employer or VHA data may not be appropriate for Medicaid populations. Medicaid enrollments include children and teens who are not in a VHA population. Private insurance enrollments likely contain fewer individuals with serious mental illness than a Medicaid population that includes individuals eligible due to disability caused by serious

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mental illness. Consequently, we developed mental health diagnosis-based models specific to a Medicaid population.

The purpose of this study was to compare methods for predicting who is at risk for high mental health care costs. In particular, prior cost was compared with mental health diagnosis-based models using a sample of Medicaid beneficiaries. The focus is on Medicaid because it represents an important component of state expenditures, behavioral health represents 21% to 24% total Medicaid expenditures [14] and over 30% of costs among high-cost cases [9].

Methods

Data

Florida Medicaid enrollment and claims files from July 2002 through June 2005 (state fiscal years 2002/2003 to 2004/2005) were the data source for this study. Critical enrollment data included beneficiary demographics (age, sex, race, and eligibility status), Medicaid coverage periods, managed care coverage periods, and third party coverage periods. Medicaid mental health costs and International Classification of Diseases, version 9 (ICD-9) diagnoses were available from inpatient, outpatient, and physician settings (throughout this article, costs refer to expenditures by the Medicare program). All services and expenditures for nonmental health services were excluded from the analysis. The sample included Medicaid beneficiaries with fee-for-service coverage for mental health care for the entire year and a mental health diagnosis. Dual eligible enrollees were excluded because Medicare pays for the majority of care.

Analytic methods–defining high cost

Three methods were used to predict who is at risk for being a high-cost case for mental health services: prior cost, a concurrent diagnosis-based model, and a prospective diagnosis-based model. First, individuals were defined as high cost if they were in the top 10% of actual mental health costs in the base period (2003/2004). We also performed the analysis using the top 5% and top 1% of expenditures with very similar conclusions to those reported below.

Second, a concurrent model was estimated relating Medicaid mental health expenditures in the base period and base period diagnoses:

$$\textit{Medicaid bh expenditures}_{it} = X_{it}\beta + \mu_{it} \quad (1)$$

where i denote individuals and t time, μ_i is normally distributed with mean zero and a homogenous variance, X includes demographics and a vector of diagnostic variables. Demographics included age (0–5, 6–13, 14–20, 21–54; 55–64 is the reference category), race (black, other; white is the reference category), gender (male), and eligibility status (Supplemental Security Income [SSI]) (the Florida Medicaid race variable has an expected number of individuals with unknown race who are likely to be Hispanic. Thus, Hispanic and unknown race were combined to create an "other" race category). The model was estimated using pooled data from 2002/2003 to 2003/2004 to maximize sample size (there were no substantive payment updates in the Florida Medicaid system, thus we did not deflate costs in the 2003/2004 data. Average costs were quite similar in the 2 years at $2938 in 2002/2003 and $2927 in 2003/2004).

Several diagnosis-based models use raw expenditures as the dependent variable in a linear ordinary least squares model. Nevertheless, expenditure data are typically right-skewed such that regression models result in implausible negative expenditure predictions, error terms that are not normally distributed, and outlier values having substantial influence on the estimated coefficients. We follow much of the recent literature and estimate generalized linear models with a gamma distribution [15,16]. Comparisons of a log and square root link using a Hosmer-Lemeshow test suggest the square root link fit the upper end of the expenditure distribution much better than a log-link [17]. One advantage of using this approach is that estimation is performed on the raw expenditure scale rather than the transformed scale. Consequently, retransformation of predictions back to the raw expenditure scale is not required.

A diagnosis-based model requires ICD-9-CM diagnoses be clustered within diagnostic groups homogeneous both clinically and in expenditures. For example, prior research has developed models using 7 diagnostic groups [11], 9 diagnostic groups [12], and 48 diagnostic groups of mental health conditions [13]. To determine diagnostic groupings for the current study, disease categories were created that included clinically-related four and five digit ICD-9-CM codes. A preliminary regression model was estimated with the detailed disease categories. Disease categories were aggregated based on clinical consultation, similar estimated coefficients for clinically-related diagnoses in the preliminary model, and small sample sizes for some disaggregated categories. The final model contained 22 diagnostic categories [18] (Table 1 includes a complete list of diagnostic categories). Two service categories were also included, targeted case management for children, and targeted case management for adults, because they act as a sign of illness severity [19,20]. Hierarchies were imposed such that, for a person, only the most serious manifestation of closely related diseases was counted. For example, if a person was coded with a severe episodic mood disorder such as "major depression" (296.2 or 296.3) and also a less serious "depressive disorder, not elsewhere classified" (311.X), only the more severe manifestation would be counted. An individual with comorbidities that were not considered closely related would have each disorder counted. For example, a person with an anxiety disorder and a conduct disorder would have both diagnoses included. All coefficients for diagnostic groups were restricted to be greater than zero (although statistical significance was not required). Diagnostic groups with negative estimated costs were removed from the regression specification. The estimated coefficients were used along with 2003/2004 characteristics and diagnoses to predict expenditures for 2003/2004. The model is additive, and predicted costs are a function of demographics and the individual's diagnostic profile.

The third method for identifying high-cost cases uses a prospective model. The prospective model estimates Medicaid mental health expenditures in the following year as a function of base year diagnoses:

$$\textit{Medicaid bh expenditure}_{i,t+1} = X_{it}\beta + \mu_{it} \quad (2)$$

A prospective model has been used to identify high-cost cases for total health care [6], and high costs were found to persist over time across mental health diagnoses [10]. To estimate the model, Medicaid expenditures for mental health services in 2003/2004 were regressed on demographics and diagnoses from 2002/2003 using individuals Medicaid enrolled in both years. Once again, a generalized linear model was estimated with a gamma distribution and square root link. The same hierarchies were used, and the standard restrictions on the coefficients were applied. The estimated coefficients were used along with 2003/2004 characteristics and diagnoses to predict expenditures for 2004/2005.

Each of the three methods was expected to predict somewhat different groups of individuals as high-cost cases. The prior cost method simply predicts that all individuals in the top decile of costs in the base year will remain in the top decile in the following year. The concurrent model predicts that individuals with high-cost diseases will be high-cost cases in the following year. The prospective model predicts that individuals with a diagnostic profile typically related to high costs in the following year will be

Table 1 – Regression results (behavioral health case mix models).

	Concurrent		Prospective	
	Coefficient	SE	Coefficient	SE
Intercept	2.91	0.60	17.89	1.05
Demographics				
Age				
0–5	14.28	0.64	19.98	1.36
6–13	18.77	0.58	21.07	1.05
14–20	13.69	0.58	15.98	1.03
21–54	2.07	0.47	3.89	0.77
Gender				
Male	0.82	0.25	2.24	0.46
Race				
Other	1.90	0.26	2.44	0.48
Black	2.86	0.30	5.22	0.59
Eligibility				
SSI	3.99	0.28	3.01	0.56
Foster care	7.76	0.46	5.87	0.81
Diagnostic groups				
Persistent mental disorders classified elsewhere	23.09	2.01	16.70	3.27
Transient mental disorders due to conditions classified elsewhere	9.37	0.94	9.19	2.37
Schizophrenic disorders	40.32	0.62	35.63	0.95
Schizophrenic disorders – chronic w/acute exacerbation	116.87	2.39	92.48	2.62
Episodic mood disorders	32.58	0.57	23.30	0.93
Episodic mood disorders – severe	23.75	0.44	13.13	0.73
Delusional disorders	19.29	4.18	8.26*	6.38
Other nonorganic psychoses	22.93	0.90	24.55	1.69
Anxiety, dissociative, and somatoform disorders	13.52	0.41	6.23	0.71
Personality disorders	31.81	2.50	31.66	3.77
Physiological malfunction arising from mental factors	18.74*	13.51	†	
Special symptoms, not elsewhere classified	2.39	0.67	†	
Eating disorders	12.60	3.08	17.05‡	8.73
Acute reaction to stress and adjustment reaction	15.43	0.40	6.20	0.67
Specific nonpsychotic mental disorders due to brain damage	6.75	1.59	†	
Depressive disorder not elsewhere classified	16.43	0.53	10.40	1.05
Conduct disorder	16.34	0.52	6.38	0.86
Disturbance of emotions specific to childhood and adolescence, unspecified	8.32	1.53	7.14‡	4.12
Disturbance of emotions specific to childhood and adolescence	19.29	0.56	8.77	0.90
Hyperkinetic syndrome of childhood	17.60	0.43	7.30	0.69
Specific delays in development	4.68	2.02	19.18	6.12
Targeted case management – children	4.67	0.89	7.50	3.06
Targeted case management – adults	22.82	2.19	33.08	5.14
Log likelihood	−418295		−229641	
Akaike Information Criterion	836658		459343	
Bayesian Information Criterion	836957		459596	

SE, standard error; SSI, Supplemental Security Income.
* The coefficient is not statistically significant at the $P < 0.05$ level.
‡ The coefficient is statistically significant at the $P < 0.1$ level; all other coefficients are significant at the $P < 0.05$ level.
† Estimated coefficient was negative and thus was removed from the specification.

high-cost cases. To determine which method(s) performed better at predicting future high-cost cases, actual expenditures for the 2004/2005 sample were compared for individuals predicted to be high cost by each model. The method that identified individuals with the highest post-period cost was considered superior. The percentage of individuals predicted to be high-cost cases who were actually in the top cost decile in the 2004/2005 sample was also reported.

In addition to comparing predictions from the three methods, predictions from combinations of the methods were also considered to determine whether predictive power could be increased over a single method. Prior research found that a combination of the prior cost and diagnosis-based methods more accurately predicted high-cost cases than either method alone [6]. Given that each method focuses on slightly different groups of people, agreement across the methods increases the likelihood that the individual will be a high-cost case in the prediction year.

Results

There were 44,426 individuals in the 2002/2003 sample, 48,755 in the 2003/2004 sample, and 50,325 in the 2004/2005 sample. The number of individuals in the 2003/2004 sample that were also in the 2004/2005 sample was 28,018. Descriptive statistics are in Table 2. The age distribution shows the majority of the sample is comprised of children and youth. Given that youth and adults

Table 2 – Variable means.

Variable	2002/2003	2003/2004	2004/2005
Age			
1–5	5.9%	10.5%	15.5%
6–12	41.1%	42.4%	42.3%
13–20	21.2%	17.1%	13.2%
21–54	26.4%	24.7%	23.9%
55–64	5.4%	5.4%	5.2%
Gender			
Female	50.9%	52.2%	52.3%
Race			
White	39.3%	37.7%	36.5%
Black	23.6%	23.5%	23.1%
Other	37.1%	38.9%	40.4%
Eligibility			
SSI	42.5%	43.2%	43.1%
Foster care	10.6%	10.1%	10.1%
Diagnostic groups			
Persistent mental disorders classified elsewhere	0.4%	0.4%	0.4%
Transient mental disorders due to conditions classified elsewhere	0.6%	0.8%	0.8%
Schizophrenic disorders	9.7%	9.7%	9.2%
Schizophrenic disorders – chronic w/acute exacerbation	2.9%	2.6%	2.7%
Episodic mood disorders	9.2%	10.2%	10.8%
Episodic mood disorders – severe	16.0%	15.2%	14.6%
Delusional disorders	0.1%	0.1%	0.1%
Other nonorganic psychoses	2.1%	2.3%	2.1%
Anxiety, dissociative, and somatoform disorders	12.5%	12.3%	11.7%
Personality disorders	1.1%	0.9%	1.0%
Physiological malfunction arising from mental factors	0.0%	0.0%	0.0%
Special symptoms, not elsewhere classified	0.8%	0.8%	0.8%
Eating disorders	0.2%	0.2%	0.2%
Acute reaction to stress and adjustment reaction	21.2%	21.3%	21.0%
Specific nonpsychotic mental disorders due to brain damage	0.2%	0.2%	0.2%
Depressive disorder not elsewhere classified	6.0%	6.2%	6.2%
Conduct disorder	8.7%	9.1%	9.2%
Disturbance of emotions specific to childhood and adolescence, unspecified	0.3%	0.4%	0.6%
Disturbance of emotions specific to childhood and adolescence	8.6%	8.7%	8.3%
Hyperkinetic syndrome of childhood	27.3%	29.1%	30.5%
Specific delays in development	0.3%	0.3%	0.3%
Targeted case management – children	0.8%	0.9%	0.7%
Targeted case management – adults	0.2%	0.2%	0.1%
Observations	44426	48755	50325

SSI, Supplemental Security Income.

may have differing costs and mental health diagnoses, and that the predictive power of diagnosis-based models may vary between children and youth, we also performed all the analyses separately for children and adults. Qualitatively, the results were the same as for the pooled sample of children and adults, and to conserve space only the pooled results are reported.

The regression results for the concurrent model are in Table 1. Among the demographic variables, younger individuals tended to have higher costs than older enrollees (55–64 years old). Men had higher costs than women, and blacks and “other” racial groups (primarily Hispanic) had higher costs than the omitted category of white. Among the diagnostic groups, some of the higher cost groups included schizophrenia, episodic mood disorders, and personality disorders. Both service categories included in the model, target case management – children and targeted case management – and adults, were associated with greater severity and higher costs.

The regression results for the prospective model are also in Table 1. Men, blacks, and “other” racial groups had higher expenses in the following year, and expenses were higher for younger age groups. Among the diagnostic groups, schizophrenia, episodic mood disorders, and personality disorders were associated with higher mental health expenditures. Diagnostic groups associated with higher base year expenditures in the concurrent model were also related to future expenditures. Targeted case management was also associated with higher expenditures in the following year. The primary difference between the concurrent and prospective models was the weaker relationship between diagnosis and future expenditures.

In Table 3, we examined combinations of the three methods using the prospective sample. Seventeen percent of the sample was classified as high cost by at least one of the methods. Among those who were classified as high cost, there was considerable variability in how people were classified by each method. For example, 1386 people were only classified as high cost by the prior cost method. Another 1855 were classified as high cost by one of the diagnosis-based methods, but not by the prior cost method. A total of 1232 people (4.4% of the sample) were classified as high cost by all three methods.

The prior cost model outperformed the diagnosis-based models at identifying high-cost individuals. Costs in 2004/2005 were

Table 3 – Distribution of people across methods for predicting high-cost cases.

Measure of high cost			People	Percent	Actual 2004/2005 cost	Percent of high cost 2004/2005
Prior cost	Concurrent risk model	Prospective risk model				
0	0	0	23,361	83.4	$ 2,309	5.0
0	0	1	397	1.4	$ 4,086	10.3
0	1	0	312	1.1	$ 3,153	7.4
0	1	1	1,146	4.1	$ 4,620	15.2
1	0	0	1,386	5.0	$ 9,547	44.5
1	0	1	72	0.3	$10,426	38.9
1	1	0	112	0.4	$ 7,002	32.1
1	1	1	1,232	4.4	$19,137	58.4
Average cost for high-cost cases						
$13,684	$10,935	$10,974				
(336)	(345)	(352)				
Percentage who were in top decile of costs in 2004/2005						
49.9%	33.9%	34.0%				

Notes: Standard errors are in parentheses. Costs given are in US dollars.

highest for individuals classified as high cost by the prior cost method ($13,684, $\chi^2 = 32.0$, $P < 0.0001$). Among the three methods, the prior cost method also had the highest proportion of people whose actual costs in 2004/2005 were in the top decile of spending (49.9%). Actual costs were highest when each of the three methods predicted an individual would be a high-cost user. Costs averaged $19,137 for such individuals, more than five times the sample mean of $3,576. One should not interpret this result to suggest, however, that the combination of models improved predictive accuracy. For example, individuals in the top 4.4% of prior year costs (i.e., the top 1232 people) had average expenditures of $20,125 in 2004/2005. Thus, a prior cost model that used a more restrictive definition for high cost predicted better than the intersection of the models, suggesting the prior cost model performed best at identifying future high-cost cases for mental health services. Information from diagnosis-based models did not add predictive power.

Discussion

Several methods are available to predict which individuals will be high-cost cases for mental health care. Such individuals may be targeted for additional intervention to improve quality of care and potentially reduce costs. The emphasis on mental health is particularly important for Medicaid programs because many have carved-out mental health benefits and provide them through private sector insurers. For example, Florida offers Medicaid mental health benefits through a prepaid mental health plan (PMHP) which, in exchange for a capitated payment, is responsible for providing mental health care to Medicaid recipients. From an evaluation perspective it is important to identify individuals at-risk for high costs to determine whether they are disadvantaged after the transition to a PMHP. For the insurer, it is potentially important to identify high-cost cases for intensive case management that may reduce the need for high cost hospitalizations.

Another potential application of a diagnosis-based model for identifying at-risk cases is when providers and/or insurers do not have detailed prior use data. In these cases, mental health evaluations may provide sufficient information and diagnostic detail to predict costs. Although this hypothesis cannot be tested using administrative databases, future research should determine whether careful initial evaluation can provide sufficient information to accurately predict costs.

The choice of method has important implications for identifying which individuals are at risk. Seventeen percent of the sample was identified as high cost by at least one of the methods. The design of any intervention for high-cost cases must carefully assess which method would identify the population most appropriate for the intervention. It was thought that prospective models would limit problems associated with identifying acute cases as high cost because acute cases, which are costly in the base year, may not have future cost implications. Thirty-one percent of individuals predicted to be high cost by the concurrent and/or prospective model were in the bottom half of the distribution of 2004/2005 costs. Only 14% of individuals predicted to be high cost by the prior use method were in the bottom half of the distribution. In addition, there is substantive variation in costs within each of the 22 diagnostic groups, with a notable number of people having low costs despite being diagnosed with an illness that typically has high costs. Such variation may result from the non-adherence to treatment often seen in individuals with serious mental illness.

The prior cost method performed better at identifying future high-cost mental health cases, which differs from prior research that examined methods for identifying high total cost cases [6]. One possibility is that the diagnosis-based models for physical health are superior to the mental health models. The predictive power (at least as measured by the R^2) of the prospective models, however, is consistent with the common physical health models. Another possible explanation is that physical health expenditures are driven to a greater extent by acute utilization than mental health expenditures. Thus, prior use may be a better predictor of future mental health expenditures than physical health. Consequently, the diagnosis-based models may perform better for identifying individuals at risk for high physical health costs, whereas prior costs perform better for mental health. In addition, the results suggest that combinations of methods did not improve predictive performance over the prior cost method, which also contrasts with research on total healthcare expenditures [6].

The diagnosis-based models presented in this article add to the small literature that develops such models for mental health. Consistent with prior research schizophrenia and other psychotic disorders, as well as major depression and personality disorders were significant contributors to mental health expenditures both concurrently and prospectively [11,13,18].

The literature often suggests that spending may be reduced for high-cost cases through proper disease management. However, once the severity of a disease reaches a point where spending is very high, it may be too late to change spending without eliminating needed care. Thus, future research should examine individuals before the time period when they became high-cost cases. Understanding how they reached the point of becoming a high-cost case may be an important question. In addition, how long individuals tend to remain high-cost cases and what occurs that reduces future spending are important questions for future research.

As with any study that uses administrative data, there are several shortcomings to the analysis. Previous research has focused on identifying high-cost individuals based on the diagnostic profile from a single year of data. This article took the same approach. Future research may examine longer time frames to address several questions. For example, an individual's actual or predicted costs may vary from year to year. Some individuals may have consistently high actual or predicted costs, while others may have them intermittently. Medicaid data are examined from a single state, and the estimated models may not generalize to all states. The ability of diagnosis-based models to predict accurately depends on the accuracy and completeness of diagnostic data. Florida Medicaid claims only allow one diagnosis on physician claims, and thus are likely to undercount secondary diagnoses.

Conclusion

This study compares the accuracy of several methods that can be used to predict who will be high-cost cases in the following year. Prior cost was the best predictor of future high costs, but diagnosis-based models also performed well and might be applied when prior cost data are lacking.

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